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APPLICATION NO.	FILING DATE	FIRST NAMED INVENTOR	ATTORNEY DOCKET NO.	CONFIRMATION NO.
10/658,623	09/09/2003	Wei Fan	YOR920030261US1	2548
28211	7590	03/17/2008	EXAMINER	
FREDERICK W. GIBB, III			STARKS, WILBERT L	
Gibb & Rahman, LLC				
2568-A RIVA ROAD			ART UNIT	PAPER NUMBER
SUITE 304				2129
ANNAPOLIS, MD 21401				
MAIL DATE		DELIVERY MODE		
03/17/2008		PAPER		

Please find below and/or attached an Office communication concerning this application or proceeding.

The time period for reply, if any, is set in the attached communication.

Office Action Summary	Application No.	Applicant(s)	
	10/658,623	FAN ET AL.	
	Examiner	Art Unit	
	Wilbert L. Starks, Jr.	2129	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

- 1) Responsive to communication(s) filed on 28 November 2007.
- 2a) This action is **FINAL**. 2b) This action is non-final.
- 3) Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

- 4) Claim(s) 1,2,4-8,10-15,17-21 and 23-26 is/are pending in the application.
- 4a) Of the above claim(s) _____ is/are withdrawn from consideration.
- 5) Claim(s) _____ is/are allowed.
- 6) Claim(s) 1-2, 4-8, 10-15, 17-21, and 23-26 is/are rejected.
- 7) Claim(s) _____ is/are objected to.
- 8) Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

- 9) The specification is objected to by the Examiner.
- 10) The drawing(s) filed on _____ is/are: a) accepted or b) objected to by the Examiner.
Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).
Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).
- 11) The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

- 12) Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).
- a) All b) Some * c) None of:
 1. Certified copies of the priority documents have been received.
 2. Certified copies of the priority documents have been received in Application No. _____.
 3. Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

- | | |
|--|---|
| 1) <input checked="" type="checkbox"/> Notice of References Cited (PTO-892) | 4) <input type="checkbox"/> Interview Summary (PTO-413) |
| 2) <input type="checkbox"/> Notice of Draftsperson's Patent Drawing Review (PTO-948) | Paper No(s)/Mail Date. _____ . |
| 3) <input type="checkbox"/> Information Disclosure Statement(s) (PTO/SB/08) | 5) <input type="checkbox"/> Notice of Informal Patent Application |
| Paper No(s)/Mail Date _____. | 6) <input type="checkbox"/> Other: _____ . |

DETAILED ACTION

Claim Rejections - 35 U.S.C. §101

1. 35 U.S.C. §101 reads as follows:

Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

the invention as disclosed in claims 1-2, 4-8, 10-15, 17-21, and 23-26 is directed to non-statutory subject matter.

2. None of the claims is limited to practical applications that indicate a specific practical utility for the claimed invention. Examiner finds that *In re Warmerdam*, 33 F.3d 1354, 31 USPQ2d 1754 (Fed. Cir. 1994) controls the 35 U.S.C. §101 issues on that point for reasons made clear by the Federal Circuit in *AT&T Corp. v. Excel Communications, Inc.*, 50 USPQ2d 1447 (Fed. Cir. 1999). Specifically, the Federal Circuit held that the act of:

...[T]aking several abstract ideas and manipulating them together adds nothing to the basic equation. *AT&T v. Excel* at 1453 quoting *In re Warmerdam*, 33 F.3d 1354, 1360 (Fed. Cir. 1994).

Examiner finds that Applicant's "history files" references are just such abstract ideas.

3. Examiner bases his position upon guidance provided by the Federal Circuit in *In re Warmerdam*, as interpreted by *AT&T v. Excel*. This set of precedents is within the

same line of cases as the *Alappat-State Street Bank* decisions and is in complete agreement with those decisions. *Warmerdam* is consistent with *State Street's* holding that:

Today we hold that *the transformation of data, representing discrete dollar amounts, by a machine through a series of mathematical calculations into a final share price*, constitutes a practical application of a mathematical algorithm, formula, or calculation because it produces ‘a useful, concrete and tangible result’ -- *a final share price momentarily fixed for recording purposes and even accepted and relied upon by regulatory authorities and in subsequent trades.* (emphasis added) *State Street Bank* at 1601.

4. True enough, that case later eliminated the “business method exception” in order to show that business methods were not *per se* nonstatutory, but the court clearly *did not go so far as to make business methods per se statutory*. A plain reading of the excerpt above shows that the Court was *very specific* in its definition of the new *practical application* that indicates a specific practical utility for the claimed invention. It would have been much easier for the court to say that “business methods were *per se* statutory” than it was to define the practical application in the case as “...the transformation of data, representing discrete dollar amounts, by a machine through a series of mathematical calculations into a final share price...”

5. The court was being very specific.

6. Additionally, the court was also careful to specify that the “useful, concrete and tangible result” it found was “*a final share price momentarily fixed for recording purposes and even accepted and relied upon* by regulatory authorities and in

subsequent trades." (i.e. the trading activity is the further practical use of the real world monetary data beyond the transformation in the computer – i.e., "post-processing activity".)

7. Applicant cites no such specific results to define a useful, concrete and tangible result. Neither does Applicant specify the associated practical application with the kind of specificity the Federal Circuit used.

8. Furthermore, in the case *In re Warmerdam*, the Federal Circuit held that:

...[T]he dispositive issue for assessing compliance with Section 101 in this case is whether the claim is for a process that goes beyond simply manipulating 'abstract ideas' or 'natural phenomena' ... As the Supreme Court has made clear, '[a]n idea of itself is not patentable, ... taking several abstract ideas and manipulating them together adds nothing to the basic equation. In re Warmerdam 31 USPQ2d at 1759 (emphasis added).

9. Since the Federal Circuit held in *Warmerdam* that this is the “dispositive issue” when it judged the usefulness, concreteness, and tangibility of the claim limitations in that case, Examiner in the present case views this holding as the dispositive issue for determining whether a claim is “useful, concrete, and tangible” in similar cases. Accordingly, the Examiner finds that Applicant manipulated a set of abstract “history files” to solve purely algorithmic problems in the abstract (i.e., what *kind* of “history files” are used? Heart rhythm data? Algebraic equations? Boolean logic problems? Fuzzy logic algorithms? Probabilistic word problems? Philosophical ideas? Even vague expressions, about which even reasonable persons could differ as to their meaning? Combinations thereof?) Clearly, a claim for manipulation of “history files” is provably even more abstract (and thereby less limited in practical application) than pure “mathematical algorithms” which the Supreme Court has held are per se nonstatutory – in fact, it *includes* the expression of nonstatutory mathematical algorithms.

10. Since the claims are not limited to exclude such abstractions, the broadest reasonable interpretation of the claim limitations includes such abstractions. Therefore, the claims are impermissibly abstract under 35 U.S.C. §101 doctrine.

11. Since *Warmerdam* is within the *Alappat-State Street Bank* line of cases, it takes the same view of “useful, concrete, and tangible” the Federal Circuit applied in *State Street Bank*. Therefore, under *State Street Bank*, this could not be a “useful, concrete and tangible result”. There is only manipulation of abstract ideas.

12. The Federal Circuit validated the use of *Warmerdam* in its more recent *AT&T Corp. v. Excel Communications, Inc.* decision. The Court reminded us that:

Finally, the decision in *In re Warmerdam*, 33 F.3d 1354, 31 USPQ2d 1754 (Fed. Cir. 1994) is not to the contrary. *** The court found that the claimed process did nothing more than manipulate basic mathematical constructs and concluded that ‘taking several abstract ideas and manipulating them together adds nothing to the basic equation’; hence, the court held that the claims were properly rejected under §101 ... Whether one agrees with the court’s conclusion on the facts, the holding of the case is a straightforward application of the basic principle that mere laws of nature, natural phenomena, and abstract ideas are not within the categories of inventions or discoveries that may be patented under §101. (emphasis added) *AT&T Corp. v. Excel Communications, Inc.*, 50 USPQ2d 1447, 1453 (Fed. Cir. 1999).

13. Remember that in *In re Warmerdam*, the Court said that this was the dispositive issue to be considered. In the *AT&T* decision cited above, the Court reaffirms that this is the issue for assessing the “useful, concrete, and tangible” nature of a set of claims under §101 doctrine. Accordingly, Examiner views the *Warmerdam* holding as the dispositive issue in this analogous case.

14. The fact that the invention is merely the manipulation of *abstract ideas* is clear. The data referred to by Applicant’s idea of “history files” is simply an abstract construct that does not provide limitations in the claims to the transformation of real world data (such as monetary data or heart rhythm data) by some disclosed process. Consequently, the necessary conclusion under *AT&T*, *State Street* and *Warmerdam*, is straightforward and clear. The claims take several abstract ideas (i.e., “history files” in the abstract) and manipulate them together adding nothing to the basic equation. Claims 1-2, 4-8, 10-15, 17-21, and 23-26 are, thereby, rejected under 35 U.S.C. §101.

Claim Rejections - 35 U.S.C. §112

The following is a quotation of the first paragraph of 35 U.S.C. §112:

The specification shall contain a written description of the invention, and of the manner and process of making and using it, in such full, clear, concise, and exact terms as to enable any person skilled in the art to which it pertains, or with which it is most nearly connected, to make and use the same and shall set forth the best mode contemplated by the inventor of carrying out his invention.

Claims 1-2, 4-8, 10-15, 17-21, and 23-26 are rejected under 35 U.S.C. §112, first paragraph because current case law (and accordingly, the MPEP) require such a rejection if a §101 rejection is given because when Applicant has not in fact disclosed the practical application for the invention, as a matter of law there is no way Applicant could have disclosed *how* to practice the *undisclosed* practical application. This is how the MPEP puts it:

(“The how to use prong of section 112 **incorporates as a matter of law** the requirement of 35 U.S.C. §101 that the specification disclose as a matter of fact a practical utility for the invention.... If the application fails as a matter of fact to satisfy 35 U.S.C. §101, then the application also fails as a matter of law to enable one of ordinary skill in the art to use the invention under 35 U.S.C. §112.”); In re Kirk, 376 F.2d 936, 942, 153 USPQ 48, 53 (CCPA 1967) (“Necessarily, compliance with §112 requires a description of how to use presently useful inventions, **otherwise an applicant would anomalously be required to teach how to use a useless invention.**”) See, MPEP 2107.01(IV), quoting In re Kirk (emphasis added).

Examiner made a §101 utility rejection of the claims because they fail to indicate a specific practical utility (i.e., practical application) for the claimed invention. Therefore, claims 1-2, 4-8, 10-15, 17-21, and 23-26 are rejected on this basis.

Claim Rejections - 35 USC § 102

1. The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

A person shall be entitled to a patent unless –

(e) the invention was described in (1) an application for patent, published under section 122(b), by another filed in the United States before the invention by the applicant for patent or (2) a patent granted on an application for patent by another filed in the United States before the invention by the applicant for patent, except that an international application filed under the treaty defined in section 351(a) shall have the effects for purposes of this subsection of an application filed in the United States only if the international application designated the United States and was published under Article 21(2) of such treaty in the English language.

2. Claims 1-2, 4-8, 10-15, 17-21, and 23-26 are rejected under 35 U.S.C. 102(e) as being anticipated by Klein (U.S. Patent Number 7,027,953; dated 11 APR 2006; class 702; subclass 184). Specifically:

Claim 1

Claim 1's "recording features of normal system operations of said computerized system in a history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After

the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: The "history file" of the prior art is used to train the classifier. The training set of the prior art anticipates this.

Claim 1's "automatically creating a model for each of said features of said normal system operations in said history file, wherein said model comprises a mathematical statement indicating what a corresponding feature equals in terms of relationships with all other features;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: the prior art discloses decision process algorithms...the "mathematical statement" claimed by Applicant.

Claim 1's "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file wherein said anomaly scores are predictive of whether each of said features will be normal according to previously defined standards when one or more of the other features are abnormal

according to previously defined standards;" is anticipated by Klein, column 2, lines 65-67 and column 3, lines 1-8, where it recites:

Every fault type of a monitored component is associated with at least one pointer, defining a frequency region of a vibrational signature in a particular domain. At each pointer, the current vibrational pattern of the component, within the observed frequency region, are compared with a baseline pattern, using preferably up to nine mathematical operators referred to as "**diagnostic indices**." The set of values provided by each index when the pointer value is entered into the index is referred to herein as a vibration feature. The index is a function that provides a result by reference to a deviation from an expected "normal."

EN: the diagnostic indices anticipate the anomaly scores.

Further, it is anticipated by Klein, column 3, lines 28-38, where it recites:

Because the system Vib-RAY is sensitive to signature changes and is focused on specific failure modes, it can distinguish between normal and abnormal states and can therefore diagnose abnormal patterns, as well as predict failures, by detecting problems at their incipient stages. The wide-band multi-domain analysis is effective in detecting cracks in blades, degraded bearings, engine compressor stall, damaged gearboxes, and improper assembly. With appropriate pointer identification and detection process, many other abnormalities can be detected, such as degraded gears and clogged nozzles.

EN: therefore, Applicant's argument that the prior art does not predict failures is incorrect.

Claim 1's "establishing a threshold to evaluate whether events in live system operations of said computerized system are anomalies as compared to said normal system operations;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defect detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domains at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the prior art threshold is the same as in Applicant's claims.

Claim 1's "automatically identifying anomalous events in said live system operations based on said anomaly scores and on said threshold;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defect detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domains at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the anomalous event in the prior art is the failing of the bearing outer race.

Claim 1's "reporting said anomalous events; and" is anticipated by Klein, column 17, lines 62-67 and column 18, lines 1-5, where it recites:

Another operation of the diagnostic sequence is verification of over limits. A verified **over limit** results in an **alert**. The system of the present invention preferably provides the following data to assist the engine expert in analyzing the over limit event and determine its criticality: a record of all parameters before, during, and after the over limit event; relevant diagnostics history of the engine; and supporting information such as the engine maintenance schedule. The diagnostic process also detects aircraft sensor failures, which are characterized by simultaneous trend shifts of a specific parameter in all of the aircraft's engines.

EN: the prior art alert is the claimed report.

Claim 1's "periodically repeating said calculating." is anticipated by Klein, column 17, lines 29-41, where it recites:

The second stage is the Feature extraction, i.e. numerical representation of the monitored parameters characteristics. The features can be parameter deviations from the initialization point (snapshot), or shift of each parameter over a number of cycles. The basic features in current use are: snapshot, short-term shifts, long-term shifts, and varying-term shifts. It should be noted that different features provide different information about the engine. For example: snapshot and short-term shifts provide information on abrupt changes, as broken valves and open bleeds. Long-term shift are more appropriate for detection of slow deterioration of engines.

EN: the prior art cycles anticipate the claimed periodically repeating.

Claim 2

Claim 2's "establishing relationships that exist between each of said features of said normal system operations;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN training establishes relationships

Claim 2's "selecting a labeled feature from said features;" is anticipated by Klein, column 18, lines 6-19, where it recites:

Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which partitions the parameters' multidimensional space into groups. Any unknown fault that is reflected in the snapshot data will be classified as Novelty until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

EN: Novelty is a label

Claim 2's "mathematically rearranging said relationships from the point of view of said labeled feature to create a solution for said labeled feature, wherein said solution

comprises a model for said labeled feature;" is anticipated by Klein, column 18, lines 6-19, where it recites:

Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which partitions the parameters' multidimensional space into groups. Any unknown fault that is reflected in the snapshot data will be classified as Novelty until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

EN: training the classifier is mathematical rearrangement.

Claim 2's "selecting different features as said labeled feature and repeating said process of mathematically rearranging said relationships to produce solutions from the point of view of each remaining feature as models for the remaining features." is anticipated by Klein, column 18, lines 6-19, where it recites:

Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which partitions the parameters' multidimensional space into groups. Any unknown fault that is reflected in the snapshot data will be classified as Novelty until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

Claim 3

Claim 3's "The method in claim 2, wherein said solution comprises a mathematical statement of what said labeled feature equals in terms of the relationships between the remaining features." is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: the algorithm is a mathematical statement.

Claim 4

Claim 4's "The method in claim 2, wherein said normal system operations comprise said features in said history file at the time said models are created." is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN : The history file is used in retraining during normal operations.

Claim 5

Claim 5's "predicting a likelihood that said each feature will be normal when one or more of the other features are abnormal, using said model of each of said features;" is anticipated by Klein, Abstract, where it recites:

A vibrational analysis system diagnosis the health of a mechanical system by reference to vibration signature data from multiple domains. Features are extracted from signature data by reference to pointer locations. The features provide an indication of signature deviation from a baseline signature in the observed domain. Several features applicable to a desired fault are aggregated to provide an indication of the **likelihood** that the fault has manifested in the observed mechanical system. The system may also be used for **trend analysis** of the health of the mechanical system.

EN: trend analysis is used to predict

Claim 5's "repeating said predicting using different presumptions about other features being normal and abnormal to produce said trained file of a plurality of anomaly scores for each of said features." is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the **update** of the airborne system or the ground station configuration, the system is able to **automatically identify the new defect**.

EN: the repeating using different assumptions is the retraining.

Claim 6

Claim 6's "The method in claim 5, wherein said trained file provides an normally score for each of said features for each of a plurality of different possible abnormalities." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the threshold is an anomaly score.

Claim 7

Claim 7's "determining values of features for a given operation of said system;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure,

the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the index is a value of a feature.

Claim 7's "referring to said trained file to retrieve an anomaly score for each of said features of said given operation;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the threshold is an anomaly score.

Claim 7's "comparing said anomaly score for each of said features of said given operation with said threshold to determine whether each anomaly score exceeds said threshold." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the

first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the threshold is an anomaly score.

Claim 8

Claim 8's "recording features of normal system operations of said computerized system in a history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: The "history file" of the prior art is used to train the classifier. The training set of the prior art anticipates this.

Claim 8's "automatically creating a model for each of said features of said normal operations in said history file, wherein said model comprises a mathematical statement indicating what a corresponding feature equals in terms of relationships with all other features;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: the prior art discloses decision process algorithms...the "mathematical statement" claimed by Applicant.

Claim 8's "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file, wherein said anomaly scores are predictive of whether each of said features will be normal according to previously defined standards when one or more of the other features are abnormal according to previously defined standards;" is anticipated by Klein, column 2, lines 65-67 and column 3, lines 1-8, where it recites:

Every fault type of a monitored component is associated with at least one pointer, defining a frequency region of a vibrational signature in a particular domain. At each pointer, the current vibrational pattern of the component, within the observed frequency region, are compared with a baseline pattern, using preferably up to nine mathematical operators referred to as "diagnostic indices." The set of values provided by each index when the pointer value is entered into the index is referred to herein as a vibration feature. The index is a function that provides a result by reference to a deviation from an expected "normal."

EN: the diagnostic indices anticipate the anomaly scores.

Further, it is anticipated by Klein, column 3, lines 28-38, where it recites:

Because the system Vib-RAY is sensitive to signature changes and is focused on specific failure modes, it can distinguish between normal and abnormal states and can therefore diagnose abnormal patterns, as well as predict failures, by detecting problems at their incipient stages. The wide-band multi-domain analysis is effective in detecting cracks in blades, degraded bearings, engine compressor stall, damaged gearboxes, and improper assembly. With appropriate pointer identification and detection process, many other abnormalities can be detected, such as degraded gears and clogged nozzles.

EN: therefore, Applicant's argument that the prior art does not predict failures is incorrect.

Claim 8's "establishing a threshold to evaluate whether events in live system operations of said computerized system are anomalies as compared to said normal system operations;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainids at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the prior art threshold is the same as in Applicant's claims.

Claim 8's "automatically identifying anomalous events in said live system operations based on said anomaly scores and on said threshold;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the anomalous event in the prior art is the failing of the bearing outer race.

Claim 8's "reporting said anomalous events; and" is anticipated by Klein, column 17, lines 62-67 and column 18, lines 1-5, where it recites:

Another operation of the diagnostic sequence is verification of over limits. A verified over limit results in an alert. The system of the present invention preferably provides the following data to assist the engine expert in analyzing the over limit event and determine its criticality: a record of all parameters before, during, and after the over limit event; relevant diagnostics history of the engine; and supporting information such as the engine maintenance schedule. The diagnostic process also detects aircraft sensor failures, which are characterized by simultaneous trend shifts of a specific parameter in all of the aircraft's engines.

EN: the prior art alert is the claimed report.

Claim 8's "periodically repeating said calculating;" is anticipated by Klein, column 17, lines 29-41, where it recites:

The second stage is the Feature extraction, i.e. numerical representation of the monitored parameters characteristics. The features can be parameter deviations from the initialization point (snapshot), or shift of each parameter over a number of cycles. The basic features in current use are: snapshot, short-term shifts, long-term shifts, and varying-term shifts. It should be noted that different features provide different information about the engine. For example: snapshot and short-term shifts provide information on abrupt changes, as broken valves and open bleeds. Long-term shift are more appropriate for detection of slow deterioration of engines.

EN: the prior art cycles anticipate the claimed periodically repeating.

Claim 8's "establishing relationships that exist between each of said features for said normal system operations;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: the claimed "establishing relationships" is anticipated by retraining of the prior art.

Claim 8's "selecting a labeled feature from said features;" is anticipated by Klein, column 18, lines 6-19, where it recites:

Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which partitions the parameters' multidimensional space into groups. Any unknown fault that is reflected in the snapshot data will be classified as Novelty until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

EN: the label in the prior art is "Novelty"

Claim 8's "mathematically rearranging said relationships from the point of view of said labeled feature to create a solution for said labeled feature, wherein said solution comprises said model for said labeled feature;" is anticipated by Klein, column 18, lines 6-19, where it recites:

Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which partitions the parameters' multidimensional space into groups. Any unknown fault that is reflected in the snapshot data will be classified as Novelty until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the

diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

EN: mathematical rearrangement is performed in the training of the classifier.

Claim 8's "selecting different features as said labeled feature and repeating said process of mathematically rearranging said relationships to produce solutions from the point of view of each remaining feature as models for the remaining features." is anticipated by Klein, column 18, lines 6-19, where it recites:

Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which partitions the parameters' multidimensional space into groups. Any unknown fault that is reflected in the snapshot data will be classified as Novelty until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

EN: The prior art label is "Novelty"

Claim 9

Claim 9's "The method in claim 8, wherein said solution comprises a mathematical statement of what said labeled feature equals in terms of the relationships between the remaining features." is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: the prior art discloses decision process algorithms...the "mathematical statement" claimed by Applicant.

Claim 10

Claim 10's "The method in claim 8, wherein said normal system operations comprise said features in said history file at the time said models are created." is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN : The history file is used in retraining during normal operations.

Claim 11

Claim 11's "predicting a likelihood that each feature will be normal when one or more of the other features are abnormal, using said model of each of said features;" is anticipated by Klein, Abstract, where it recites:

A vibrational analysis system diagnosis the health of a mechanical system by reference to vibration signature data from multiple domains. Features are extracted from signature data by reference to pointer locations. The features provide an indication of signature deviation from a baseline signature in the observed domain. Several features applicable to a desired fault are aggregated to provide an indication of the **likelihood** that the fault has manifested in the observed mechanical system. The system may also be used for **trend analysis** of the health of the mechanical system.

Claim 11's "repeating said predicting using different presumptions about other features being normal and abnormal to produce said trained file of a plurality of anomaly scores for each of said features." is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the **update** of the airborne system or the ground station configuration, the system is able to **automatically identify the new defect**.

EN :the repeating is done in the retraining

Claim 12

Claim 12's "The method in claim 11, wherein said trained file provides an normally score for each of said features for each of a plurality of different possible abnormalities." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainids at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

Claim 13

Claim 13's "determining values of features for a given operation of said system;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainids at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

Claim 13's "referring to said trained file to retrieve an anomaly score for each of said features of said given operation;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the threshold is an anomaly score.

Claim 13's "comparing said anomaly score for each of said features of said given operation with said threshold to determine whether each anomaly score exceeds said threshold." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the threshold is an anomaly score.

Claim 14

Claim 14's "recording features of normal system operations of said computerized system in a history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: The "history file" of the prior art is used to train the classifier. The training set of the prior art anticipates this.

Claim 14's "automatically creating a model for each of said features of said normal system operations in said history file, wherein said model comprises a mathematical statement indicating what a corresponding feature equals in terms of relationships with all other features;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the

airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: the prior art discloses decision process **algorithms**...the "mathematical statement" claimed by Applicant.

Claim 14's "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file, wherein said anomaly scores are predictive of whether each of said features will be normal according to previously defined standards when one or more of the other features are abnormal according to previously defined standards;" is anticipated by Klein, column 2, lines 65-67 and column 3, lines 1-8, where it recites:

Every fault type of a monitored component is associated with at least one pointer, defining a frequency region of a vibrational signature in a particular domain. At each pointer, the current vibrational pattern of the component, within the observed frequency region, are compared with a baseline pattern, using preferably up to nine mathematical operators referred to as "**diagnostic indices**." The set of values provided by each index when the pointer value is entered into the index is referred to herein as a vibration feature. The index is a function that provides a result by reference to a deviation from an expected "normal."

EN: the diagnostic indices anticipate the anomaly scores.

Further, it is anticipated by Klein, column 3, lines 28-38, where it recites:

Because the system Vib-RAY is sensitive to signature changes and is focused on specific failure modes, it can distinguish between normal and abnormal states and can therefore diagnose abnormal patterns, as well as predict failures, by detecting problems at their incipient stages. The wide-band multi-domain analysis is effective in detecting cracks in blades, degraded bearings, engine compressor stall, damaged

gearboxes, and improper assembly. With appropriate pointer identification and detection process, many other abnormalities can be detected, such as degraded gears and clogged nozzles.

EN: therefore, Applicant's argument that the prior art does not predict failures is incorrect.

Claim 14's "establishing a threshold to evaluate whether events in live system operations of said computerized system are anomalies as compared to said normal system operations;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defect detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domains at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the prior art threshold is the same as in Applicant's claims.

Claim 14's "automatically identifying anomalous events in said live system operations based on said anomaly scores and on said threshold;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defect detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domains at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the **likelihood that the bearing outer race is failing**. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the anomalous event in the prior art is the failing of the bearing outer race.

Claim 14's "reporting said anomalous events; and" is anticipated by Klein, column 17, lines 62-67 and column 18, lines 1-5, where it recites:

Another operation of the diagnostic sequence is verification of over limits. A verified **over limit results in an alert**. The system of the present invention preferably provides the following data to assist the engine expert in analyzing the over limit event and determine its criticality: a record of all parameters before, during, and after the over limit event; relevant diagnostics history of the engine; and supporting information such as the engine maintenance schedule. The diagnostic process also detects aircraft sensor failures, which are characterized by simultaneous trend shifts of a specific parameter in all of the aircraft's engines.

EN: the prior art alert is the claimed report.

Claim 14's "periodically repeating said calculating;" is anticipated by Klein, column 17, lines 29-41, where it recites:

The second stage is the Feature extraction, i.e. numerical representation of the monitored parameters characteristics. The features can be parameter deviations from the initialization point (snapshot), or shift of each parameter over a number of cycles. The basic features in current

use are: snapshot, short-term shifts, long-term shifts, and varying-term shifts. It should be noted that different features provide different information about the engine. For example: snapshot and short-term shifts provide information on abrupt changes, as broken valves and open bleeds. Long-term shift are more appropriate for detection of slow deterioration of engines.

EN: the prior art cycles anticipate the claimed periodically repeating.

Claim 14's "predicting a likelihood that each feature will be normal when one or more of the other features are abnormal, using said model of each of said features;" is anticipated by Klein, Abstract, where it recites:

A vibrational analysis system diagnosis the health of a mechanical system by reference to vibration signature data from multiple domains. Features are extracted from signature data by reference to pointer locations. The features provide an indication of signature deviation from a baseline signature in the observed domain. Several features applicable to a desired fault are aggregated to provide an indication of the likelihood that the fault has manifested in the observed mechanical system. The system may also be used for trend analysis of the health of the mechanical system.

EN: trend analysis in the prior art is used to predict.

Claim 14's "repeating said predicting using different presumptions about other features being normal and abnormal to produce said trained file of a plurality of anomaly scores for each of said features." is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural

networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: repeating using different assumptions is anticipated by retraining.

Claim 15

Claim 15's "establishing relationships that exist between each of said features for said normal system operations;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: training the system establishes relationships.

Claim 15's "selecting a labeled feature from said features; " is anticipated by Klein, column 18, lines 6-19, where it recites:

Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which partitions the parameters' multidimensional space into groups. Any unknown fault that is reflected in the snapshot data will be classified as Novelty until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The

principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

Claim 15's "mathematically rearranging said relationships from the point of view of said labeled feature to create a solution for said labeled feature, wherein said solution comprises a model for said labeled feature;" is anticipated by Klein, column 18, lines 6-19, where it recites:

Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which partitions the parameters' multidimensional space into groups. Any unknown fault that is reflected in the snapshot data will be classified as Novelty until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

Claim 15's "selecting different features as said labeled feature and repeating said process of mathematically rearranging said relationships to produce solutions from the point of view of each remaining feature as models for the remaining features." is anticipated by Klein, column 18, lines 6-19, where it recites:

Snapshot diagnostics uses a Fuzzy ART (Adaptive Resonance Theory) neural network. This is preferably an unsupervised learning classifier, which partitions the parameters' multidimensional space into groups. Any unknown fault that is reflected in the snapshot data will be

classified as Novelty until the expert identifies the fault. This classifier continuously improves as more data and feedback are accumulated. The principle of the trend diagnostics is to detect relative changes of the parameters .DELTA. in respect to previous measurements. The automatic diagnostics sequence is combined from features extracting, multi classification methods and finally decision processes that determine the engine condition and the confidence level of the diagnostics. The novelty detection method is preferably used to affirm the classifier's results.

EN: Novelty is a label

Claim 16

Claim 16's "The method in claim 15, wherein said solution comprises a mathematical statement of what said labeled feature equals in terms of the relationships between the remaining features." is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: the algorithm is a mathematical statement

Claim 17

Claim 17's "The method in claim 15, wherein said normal system operations comprise said features in said history file at the time said models are created." is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the **update** of the airborne system or the ground station configuration, the system is able to **automatically identify the new defect.**

EN : The history file is used in retraining during normal operations.

Claim 18

Claim 18's "The method in claim 14, wherein said trained file provides a normally score for each of said features for each of a plurality of different possible abnormalities." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defect detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domains at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: The threshold is a score.

Claim 19

Claim 19's "determining values of features for a given operation of said system;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: The index result is a value for a feature

Claim 19's "referring to said trained file to retrieve an anomaly score for each of said features of said given operation;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defecr detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domainds at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the threshold is an anomaly score.

Claim 19's "comparing said anomaly score for each of said features of said given operation with said threshold to determine whether each anomaly score exceeds said threshold." is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defect detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domains at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

Claim 20

Claim 20's "recording features of normal operations of said computerized system in a history file;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: The "history file" of the prior art is used to train the classifier. The training set of the prior art anticipates this.

Claim 20's "automatically creating a model for said each of said features of said normal system operations in said history file, wherein said model comprises a mathematical statement indicating what a corresponding feature equals in terms of relationships with all other features;" is anticipated by Klein, column 23, lines 54-64, where it recites:

The retraining process depends on the specific decision or classification algorithm. For supervised learning techniques (neural networks) the training process is initiated when adding the new patterns to the training set. For expert systems new rules are added to the rule base. In the case of Fuzzy ART algorithms the appropriate class is identified. After the retraining of the system, sets of new parameters for the decision process algorithms are obtained. After the update of the airborne system or the ground station configuration, the system is able to automatically identify the new defect.

EN: the prior art discloses decision process algorithms...the "mathematical statement" claimed by Applicant.

Claim 20's "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file wherein said anomaly scores are predictive of whether each of said features will be normal according to previously defined standards when one or more of the other features are abnormal according to previously defined standards;" is anticipated by Klein, column 2, lines 65-67 and column 3, lines 1-8, where it recites:

Every fault type of a monitored component is associated with at least one pointer, defining a frequency region of a vibrational signature in a particular domain. At each pointer, the current vibrational pattern of the

component, within the observed frequency region, are compared with a baseline pattern, using preferably up to nine mathematical operators referred to as "**diagnostic indices**." The set of values provided by each index when the pointer value is entered into the index is referred to herein as a vibration feature. The index is a function that provides a result by reference to a deviation from an expected "normal."

EN: the diagnostic indices anticipate the anomaly scores.

Further, it is anticipated by Klein, column 3, lines 28-38, where it recites:

Because the system Vib-RAY is sensitive to signature changes and is focused on specific failure modes, it can distinguish between normal and abnormal states and can therefore diagnose abnormal patterns, as well as predict failures, by detecting problems at their incipient stages. The wide-band multi-domain analysis is effective in detecting cracks in blades, degraded bearings, engine compressor stall, damaged gearboxes, and improper assembly. With appropriate pointer identification and detection process, many other abnormalities can be detected, such as degraded gears and clogged nozzles.

EN: therefore, Applicant's argument that the prior art does not predict failures is incorrect.

Claim 20's "establishing a threshold to evaluate whether events in live system operations of said computerized system are anomalies as compared to said normal system operations;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defect detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domains at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure mode are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the

analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the prior art threshold is the same as in Applicant's claims.

Claim 20's "automatically identifying anomalous events in said live operations based on said anomaly scores and on said threshold;" is anticipated by Klein, column 27, lines 13-15 and column 28, lines 1-10, where it recites:

As indicated in Table B, for the engine bearing outer race defect detection, the diagnostic indexes of Amn, Gmn, Hmn, Mfrms, So, and Rdo are calculated in the Orders and Envelope orders domains at the first 3 odd harmonies and at the first 3 sidebands. Finally, all diagnostic indexes belonging to a particular failure node are aggregated using their relative weights, as provided in Table A, in the relevant domains. This aggregate feature provides an indication of component health for the analyzed fault condition. Hence, for the main bearing outer race failure, the aggregate feature would indicate the likelihood that the bearing outer race is failing. In one embodiment, this indication is by observing that the aggregate index result exceeds a threshold level.

EN: the anomalous event in the prior art is the failing of the bearing outer race.

Claim 20's "reporting said anomalous events; and" is anticipated by Klein, column 17, lines 62-67 and column 18, lines 1-5, where it recites:

Another operation of the diagnostic sequence is verification of over limits. A verified over limit results in an alert. The system of the present invention preferably provides the following data to assist the engine expert in analyzing the over limit event and determine its criticality: a record of all parameters before, during, and after the over limit event; relevant diagnostics history of the engine; and supporting information such as the engine maintenance schedule. The diagnostic process also

detects aircraft sensor failures, which are characterized by simultaneous trend shifts of a specific parameter in all of the aircraft's engines.

EN: the prior art alert is the claimed report.

Claim 20's "periodically repeating said calculating." is anticipated by Klein, column 17, lines 29-41, where it recites:

The second stage is the Feature extraction, i.e. numerical representation of the monitored parameters characteristics. The features can be parameter deviations from the initialization point (snapshot), or shift of each parameter over a number of cycles. The basic features in current use are: snapshot, short-term shifts, long-term shifts, and varying-term shifts. It should be noted that different features provide different information about the engine. For example: snapshot and short-term shifts provide information on abrupt changes, as broken valves and open bleeds. Long-term shift are more appropriate for detection of slow deterioration of engines.

EN: the prior art cycles anticipate the claimed periodically repeating.

Response to Arguments

3. Applicant's arguments filed 11/28/2007 have been fully considered but they are not persuasive. Specifically:

Argument 1

Independent claims 1, 8, 14 and 20 each include the claim limitations of "recording features of normal system operations in a history file," "creating a model for each of said features of said normal system operations in said history file," and "reporting said anomalous events." These limitations imply that during normal system operations features of the system are determined and anomalous events are reported in some manner. The features are then recorded (e.g., as historical data) in a

history file. Then, for each feature in the history file, a model is created. This aspect of the invention is explained in detail throughout the disclosure. For example, the Abstract provides that the system records actions performed as features in a history file and automatically creates a model for each feature. Paragraphs [0006] and [0023] provide that the invention begins with historical data maintained in a history file and that a model is created for each feature only from normal data in the history file. Paragraph [0020] references a dataset of N features from which N models are created. Therefore, the Applicants submit that contrary to the Examiner's finding the "history files" are not just abstract ideas, but rather contain real world data (i.e., a recording of features of normal system operations) from which models are created (i.e., a model is created for each feature of normal system operations that is recorded).

Applicant did not claim what kind of model is used, nor did Applicant claim how it is trained. Artificial intelligence "classifiers" and "models" are "universal function approximators." It is that property that permits them to handle nonlinear operations. As such, the mere claim for a model does not specify which model or what that model is trained to do.

Therefore, Applicant seeks to patent the transformation of any data in any way to achieve any result.

A claim for "anomalous data" simply means that there are two primary classes determined by the "model." In-class data (so-called "normal data") and out of class data (so called "anomalous data"). There are many such models: 1) hyperplane classifiers, 2) support vector machines, 3) certain fuzzy logic systems, etc. Again, each of them, if properly trained, can be universal function approximators.

If the algorithms are trained with real-world data, then the classes of functions that they approximate could be defined. Applicant's recital of "history files" is insufficient to do this.

Applicant has failed to carry his burden on this point. The rejections stand.

Argument 2

Furthermore, if, as indicated by the Examiner, the data referred to by the "history files" is simply an abstract construct that did not provide limitations in the claims to the transformation of real world data by some disclosed process, it was still incumbent upon the Examiner to determine whether the method otherwise produces a useful, concrete or tangible result. That is, it is generally understood that to establish utility under 35 U.S.C. §101 method inventions as a whole must produce a "useful, concrete and tangible result." (see State Street, 149 F.3d at 1373-74, 47 USPQ2d at 1601-02). Additionally, AT&T Corp v. Excel Communications, Inc. 172 F.3d 1352, 1358-59, 50 USPQ2d 1447, 1452 (Fed. Cir. 1999) provides that physical transformation "is not an invariable requirement, but merely one example, of how a mathematical algorithm [or law of nature] may bring about a useful application." If the Examiner determines that there is no physical transformation, additional review is required to determine if the claim provides a useful, tangible and concrete result. The review by the Examiner should focus not on each step, but on whether the final result achieved by the claimed invention is "useful, concrete and tangible" (see AT&T 172 F.3d at 1358-5).

The Applicants submit that the results of the method embodiments disclosed are "useful." Specifically, the Applicants submit that a credible, specific, and substantial use for the method of the invention (namely identifying and reporting anomalous events that occur during system operations) is readily apparent and well-established in the independent claims themselves. That is, each of the independent claims provides for a method of automatically identifying and reporting anomalous situations that occur during system operations. The limiting features in each of the claims include, but are not limited to, the following: (1) "recording features of normal system operations in a history file;" (2) "automatically creating a model for each of said features of said normal system operations in said history file;" (3) "calculating anomaly scores of said features of said normal system operations and storing said anomaly scores in a trained file;" (4) "establishing a threshold to evaluate whether events in live system operations are anomalies as compared to said normal system operations;" (5) "automatically identifying anomalous events in said live system operations based on said anomaly scores and on said threshold;" (6) "reporting said anomalous events;" and (7) "periodically repeating said calculating."

The uses have not been specified at all. Further, unspecified uses cannot be assumed to be credible. Since the scope of Applicant's claims is undefined, non-credible uses have not been excluded from the metes and bounds of the claims. Specifically, applications to perpetual motion machines, cold fusion systems, and

antigravity machines are well within the breadth of scope of Applicant's claims, but those uses are hardly credible. Applicant's argument is not persuasive and the rejections stand.

Argument 3

Independent claim 8 further includes the additional limiting features of ""wherein said creating of said model for each of said features comprises: establishing relationships that exist between each of said features for said normal system operations; selecting a labeled feature from said features; mathematically rearranging said relationships from the point of view of said labeled feature to create a solution for said labeled feature, wherein said solution comprises a model for said labeled feature; selecting different features as said labeled feature and repeating said process of mathematically rearranging said relationships to produce solutions from the point of view of each remaining feature as models for the remaining features." Independent claim 14 further includes the additional limiting features of "wherein said calculating comprises: predicting a likelihood that each feature will be normal when one or more of the other features are abnormal, using said model of each of said features; repeating said predicting using different presumptions about other features being normal and abnormal to produce said trained file of a plurality of anomaly scores for each of said features." Those skilled in the art would immediately appreciate why the invention is useful (i.e., would appreciate why it is important to be able to identify when anomalous events occur during system operations and to report out the occurrence of those anomalous events). For example, as set out in paragraph [0063] of the specification, the invention, which identifies and reports anomalous events, can be applicable to self-diagnosis, anomaly detection, outlier detection and skewed distribution data mining (i.e., it is useful in a number of different applications.)

Applicant admits that some of the limitations of the claims include "wherein said creating of said model for each of said features comprises: establishing relationships that exist between each of said features..." This is what Examiner meant earlier about classifiers being universal function approximators. Applicant admits that "relationships" are established between data. That is called a function or equation. Applicant did not specify the class of equations being modeled. Thus, Applicant seeks to patent the

transformation of any data in any way to achieve any result. Applicant's argument is not persuasive and the rejections stand.

Argument 4

More specifically, credible, specific, and substantial uses for the method of the invention (namely identifying and reporting anomalous events that occur during live system operations) are asserted throughout the specification. Paragraph [0004] provides that in order to achieve a goal of autonomic computing it is important that a target system be able to perform self-diagnosis. Per paragraph [0018], the claimed invention provides a general solution to conventional problems associated with self-diagnosis by providing a method that uses an additive approach to combine evidence from multiple sources (i.e., history files) and then uses a probabilistic thresholding approach to detect anomalies. These detected anomalies can be reported to a system user (see paragraph [0063]). Paragraph [0063] provides that the invention applicable to self-diagnosis, anomaly detection, outlier detection and skewed distribution data mining (i.e., it is useful in a number of different applications.) and further detail in what manner it is applicable. Per paragraph [0064], the claimed invention is superior to prior art systems because it takes advantage of inter-feature correlation and predicts the value of one feature using values of other features and because it uses a threshold to predict anomalies.

Applicant's claims are not in means-plus function format. Nor are the method claims in step-for format. Therefore, 112, sixth paragraph has not been invoked and the limitations of the Specification cannot be "read-into" the claims. Applicant's argument is not persuasive and the rejections stand.

Argument 5

Furthermore, the Applicants submit that the results of the method embodiments disclosed are not only useful, but "tangible" and "concrete." Specifically, the claim limitations of "identifying anomalous events in said live system operations" and "reporting said anomalous events" are beneficial real-world results of performing the method of the invention (i.e., they are tangible and not abstract results, see *Gottschalk v. Benson*, 409 U.S. 63, 71-72, 175 USPQ 673, 676 (1972)). That is, as system operations occur, the method is able to identify anomalous

events that occur and to report out those events. The process steps are not abstract or theoretical. Additionally, the claim limitations of "identifying anomalous events in said live system operations" and "reporting said anomalous events" are substantially repeatable (i.e., concrete, see *In re Swartz*, 232 F.3d 862, 864, 56 USPQ2d 1703, 1704 (Fed. Cir. 2000). That is, as the live system operations proceed, the method will be able to identify and report out each anomalous event that occurs. The identification process is based on the previously calculated anomaly scores and previously established threshold. To ensure that the anomalous events will continue to be properly identified throughout the live system operations, the claim limitation of periodically recalculating the anomaly scores is also included.

Therefore, independent claims 1, 8, 14 and 20 are directed to statutory subject matter under 35 U.S.C. §101. Further, dependent claims 2-7, 9-13, 14-19 and 21-26 are similarly patentable, not only by virtue of their dependency from a patentable independent claim, but also by virtue of the additional features of the invention they define. Moreover, the Applicants note that all claims are properly supported in the specification and accompanying drawings. In view of the foregoing, the Examiner is respectfully requested to reconsider and withdraw the rejections.

The scope of "anomalous events" does not necessarily relate to data regarding "tangible" and "concrete" things. Again, an "anomalous event" could be the operation of a perpetual motion machine. Since such things do not exist, they are hardly concrete or tangible. They are notional. Applicant's argument is not persuasive and the rejections stand.

Argument 6

II. The 35 U.S.C. §112, Second Paragraph, Rejection

The Office Action provides that claims 1-26 are rejected under 35 U.S.C. § 112, first paragraph because the current case law (and accordingly, the MPEP) require such a rejection if a § 101 rejection is given because when Applicant has not in fact disclosed the practical application for the invention, as a matter of law there is no way Applicant could have disclosed how to practice the undisclosed practically application. *State Street*, 149 F.3d at 1373-74, 47 USPQ2d at 1601-02 provides that to be eligible for patent protection, the claimed invention as a whole must accomplish a practical application (i.e., it must produce a "useful, concrete and tangible result"). As discussed in detail above with regard to the rejection of claims 1-26 under 35 U.S.C. §101 the claimed invention does produce such concrete and tangible result, namely "identifying anomalous events in said live system operations" and

"reporting said anomalous events". Further, as discussed in detail above, this concrete and tangible result can be applicable to self-diagnosis, anomaly detection, outlier detection and skewed distribution data mining (i.e., it is useful in a number of different applications.) Given the fact that the only basis for the rejection of claims 1-26 under 35 U.S.C. § 112 is the existence of the rejection of those claims under 35 U.S.0 §101 rejections, the Examiner is respectfully requested to reconsider and withdraw the rejections.

Examiner reads the claims as a whole to carefully search for actual limitations to practical applications and finds none. It is Examiner's opinion that the claims are devoid of statutory material. Having been given ample opportunity to respond by amendment, Applicant has presented no other statutory limitations to circumscribe the metes and bounds of the claims sufficiently to change this assessment.

Since Applicant failed to claim a practical utility (that is, a practical application) for the invention, Applicant's claims fail the utility requirement of section 101. Since Applicant's claims failed, as a matter of fact to satisfy section 101's practical utility requirement, Applicant's claims also fail as a matter of law to satisfy the 112, first paragraph requirement.

On this basis, Examiner finds Applicant's argument to be unpersuasive and the rejections stand.

Argument 7

III. The Prior Art Rejections

Claims 1-26 stand rejected under 35 U.S.C. § 102(e) as being anticipated by Klein (U.S. Patent No. 7,027,953). Applicants respectfully traverse these rejections based on the following discussion. Specifically, the Applicants submit that Klein does not teach or suggest the following patentable features of amended independent claims 1, 8, 14 and 20: (1) "A method of automatically identifying anomalous situations during operations of a computerized system;" (2) "automatically creating a model for each of said features of said normal

operations in said history file, wherein said model comprises a mathematical statement indicating what a corresponding feature equals in terms of relationships with all other features;" (3) "calculating anomaly scores of said features of said normal operations and storing said anomaly scores in a trained file, wherein said anomaly scores are predictive of whether each of said features will be normal when one or more of the other features are abnormal;" and (4) "automatically identifying anomalous events in said live operations based on said anomaly scores and on said threshold;"

This portion of Applicant's argument is merely conclusory.

No actual differences over the prior art have been explained. Applicant's argument is unpersuasive and the rejections stand.

Argument 8

More specifically, Klein does not teach or suggest the claimed method "of automatically identifying anomalous situations during operations of a computerized system". Rather, per the claims, Klein teaches a health maintenance system for a mechanical system (see independent claim 1), a health prognosis method for a mechanical system (see independent claim 4), a method for providing a health indication for a mechanical system (see independent claim 12) and a computer implemented health diagnostic system for a mechanical system (see independent claim 14). That is, each of the embodiments of Klein refer to a method/system for diagnosing or maintaining the health of a mechanical system, not for identifying anomalous situations that occur during the operation of a computerized system, as claimed in the present invention.

Applicant points out a "distinction without a difference." The abstract of the prior art recites the following:

The features provide an indication of signature deviation from a baseline signature in the observed domain.

The signature deviation is an "anomalous situation." The regular operation of the system is represented by the "baseline signature." Applicant's claimed novelty is a

central principle of the cited prior art. Applicant's argument is unpersuasive and the rejections stand.

Argument 9

Specifically, an overview of the three-stage diagnostic method of Klein is provided at col. 6, lines 14-45. That is, the first stage of Klein is engine vibration data processing, which includes data evaluation, outlier's elimination (elimination of clearly invalid data) and trend smoothing. The second stage is feature extraction, where that features are snapshot, short-term shifts, long-term shifts and varying-term shifts, each of which provide different information about an engine. The third stage is classification, where each of the features is classified by several diagnostic methods. Figure 5 and the associated text at col. 9, lines 20-67, describe these stages in more detail. That is, in the first stage, normal and defective vibration signatures are stored 440. Furthermore, vibration data is collected and new signatures are created 450. In the second stage, features are extracted from the newly created signatures and compared with the features of known signatures 470. If a novel pattern of features is detected in a newly created signature, a new diagnostic cycle (i.e., the third stage) is triggered 480.

The Office Action cites col. 23, lines 54-63, of Klein as disclosing both the features of "**recording features of normal operations a history file**" and "**automatically creating a model for each of said features of said normal operations**". The **Applicants respectfully disagree**. As mentioned above, Figure 5, item 440, and the associated text, indicate that both **normal signatures** and defective signatures are stored. However, the cited portion of Klein does not disclose that **models** are automatically created for each of the features of normal operations, much less that such models comprise a **mathematical statement** indicating what a corresponding feature equals in terms of relationships with all other features. That is, as discussed above with regard to Figure 5, both normal and defective vibration signatures are stored and, then, during subsequent operation of the mechanical system (e.g., the engine) vibration data is collected, new signatures are created and the features of the new signatures are compared to known signatures. At col. 23, lines 40-54, Klein explains that once a novel signature is detected, the system is retrained so that the detected anomaly is considered a "known" defect for subsequent processing. The cited portion of Klein (i.e., col. 23, lines 40-54) refers to how this **retraining is performed**. Nowhere in Klein does it teach or discuss that **models are created for each feature of normal operations** or, more particularly, that these models are **mathematical statements** indicating what a corresponding feature equals in terms of relationships with all other features of normal operations that are stored in the history file.

First, as shown in the Abstract (and throughout the prior art), Applicant's "anomalies" are anticipated by the signature deviation in the prior art. As the prior art says in its Abstract:

The features provide an indication of signature deviation from a baseline signature in the observed domain.

The "signature deviation" anticipates Applicant's "anomalous situation." The regular operation of the prior art system is represented by the "baseline signature." Applicant's claimed novelty is a central principle of the cited prior art.

Secondly, Applicant seeks to draw a distinction between stored signatures and models. That is erroneous. They are the same thing. A classifier stores signatures and matches them to input data...this is a model. This is again the universal function approximation that classifiers perform. That approximated function is a "model." It is also a "mathematical statement" that Applicant asserts is not present in the prior art. Applicant merely claims a standard classifier. Nothing more.

Thirdly, Applicant admits that the prior art retrains but asserts that models are not created. Again, this is a distinction without a difference. Retraining is performed to add to and update models in the classifier in the prior art. It is the matching of the input data with the output data that is the mathematical relation in the prior art. It is a mathematical statement.

Applicant's argument is unpersuasive and the rejections stand.

Argument 10

The Office Action cites col. 2, lines 65-67 and col. 3, lines 1-8, of Klein as teach the feature of "calculating anomaly scores of said features". The Applicants respectfully disagree. The cited portion of Klein refers to the fact that vibration signatures in different domains are indicative of different types of faults. Every fault type is associated with a pointer that defines a frequency region of a vibrational pattern. The vibrational pattern is compared to a baseline pattern for that fault type to produce an index which indicates a deviation from an expected normal pattern for that fault type. In other words, for a given fault type, Klein compares a collect vibration pattern to a previously established baseline to determine if the collected patter is normal and, more specifically, how far it deviates from normal. Contrarily, calculating feature of the present invention relates to stored features of normal operation and, more specifically, calculating anomaly scores of said features, wherein the anomaly scores are predictive of whether each of the features will be normal when one or more of the other features are abnormal. The indices of Klein reflect how abnormal a collected vibration signature, relative to normal, not how likely it is to be normal when others are abnormal. Nowhere does Klein teach or disclose "calculating anomaly scores of said features of said normal operations and storing said anomaly scores in a trained file, wherein said anomaly scores are predictive of whether each of said features will be normal when one or more of the other features are abnormal."

Applicant did not claim that it is "predictive" (see claims 8 and 20, third clauses in the bodies of the claims.) Applicant "quotes" things that are not in the claims. The prior art properly anticipates the claims.

Applicant's argument is unpersuasive and the rejections stand.

Argument 11

The Office Action cites col. 27, lines 13-15 and col. 28, lines 1-10 of Klein as disclosing the feature of "automatically identifying anomalous events in said live operations based on said anomaly scores and on said threshold." The Applicants respectfully disagree. Columns 27-28 describe the feature extraction process, wherein the actual signature of the system is compared to a baseline. The comparison is performed by calculating a set of diagnostic indexes for each predefined pointer in a failure pattern. The diagnostic indexes are aggregated using relative weights and an aggregate feature provides an indication of the health of the analyzed fault conditions, when compared to a threshold level. In the present invention, an event that is detected during live system operations is identified as anomalous or not based on a threshold, but also based on anomalous scores (which as discussed above are predictive in light of other features being abnormal). Nowhere does Klein teach or disclose "automatically identifying anomalous events in said live operations based on said anomaly scores and on said threshold."

First, Applicant uses the word "calculating" in reference to the prior art. This is a party admission that the prior art is mathematical in nature, thus admitting Examiner's point in the arguments above that the model in the prior art is in fact a "mathematical statement." Applicant also admits that the prior art compares the signature of the system to a baseline. This comparison is in order to detect deviations from the baseline, as Examiner has argued above. This is how "anomalous events" (i.e., deviations from the baseline are automatically detected.)

Applicant's argument is unpersuasive and the rejections stand.

Argument 12

Therefore, the Applicants submit that independent claims 1, 8, 14 and 20 are patentable over Klein. Furthermore, dependent claims 2-7, 9-13, 14-19 and 21-26 are similarly patentable, not only by virtue of their dependency from a patentable independent claim, but also by virtue of the additional features of the invention they define. Moreover, the Applicants note that all claims are properly supported in the specification and accompanying

drawings. In view of the foregoing, the Examiner is respectfully requested to reconsider and withdraw the rejections.

Applicant's argument s regarding the independent claims was unpersuasive and the rejections of those claims stand. Accordingly, the defects in the dependent claims have not been cured.

Applicant's argument is unpersuasive and the rejections stand.

Conclusion

THIS ACTION IS MADE FINAL. Applicant is reminded of the extension of time policy as set forth in 37 CFR 1.136(a).

A shortened statutory period for reply to this final action is set to expire THREE MONTHS from the mailing date of this action. In the event a first reply is filed within TWO MONTHS of the mailing date of this final action and the advisory action is not mailed until after the end of the THREE-MONTH shortened statutory period, then the shortened statutory period will expire on the date the advisory action is mailed, and any extension fee pursuant to 37 CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event, however, will the statutory period for reply expire later than SIX MONTHS from the mailing date of this final action.

Any inquiry concerning this communication or earlier communications from the Examiner should be directed to Wilbert L. Starks, Jr. whose telephone number is (571) 272-3691.

Art Unit: 2129

Alternatively, inquiries may be directed to the following:

S. P. E. David Vincent **(571) 272-3080**

Official (FAX) **(571) 273-8300**

/Wilbert L. Starks, Jr./

Primary Examiner, Art Unit 2129

WLS

03 MAR 2007